

Using Learning Design to Unleash the Power of Learning Analytics

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New learning technologies require designers and faculty to take a fresh approach to the design of the learner experience. Adaptive learning, and responsive and predicative learning systems, are emerging with advances in learning analytics. This process of collecting, measuring, analysing and reporting data has the intention of optimising the student learning experience itself and/or the environment in which the experience of learning occurs. However, it is suggested here that no matter how sophisticated the learning analytics platforms, algorithms and user interfaces may become, it is the fundamentals of the learning design, exercised by individual learning designers and faculty, that will ensure that technology solutions will deliver significant and sustainable benefits. This paper argues that effective learning analytics is contingent on well structured and effectively mapped learning designs.

Keywords: Learning analytics, learning design, SOLE Model, visualisation

Learning Design Context

To consciously misparaphrase American satirist Tom Lehrer, learning analytics are a little 'like a sewer, you only get out of them, what you put into them'.

Anyone who has ever designed a survey instrument knows that the quality of the data you get out depends on the quality of the structured instrument used to capture that data. Regardless of the excessive hyperbole around learning analytics by ill-fitted technology solution providers, the current mobile, social and saturated data environment in which we now work, live and learn (Siemens & Matheos, 2010) doubtless represents opportunities. For these PLEN to deliver on the promises of tailoring individual learning experiences, not just to competences and learning preferences but also to life contexts, we need to design learning capable of leveraging sophisticated learning analytics. We need to enable learning designers, often faculty, with the ability generate designs that are compatible with emerging analytical technologies.

I think it important to differentiate fields of enquiry to be clear what is included and excluded across three definable educational realms, described as academic analytics (AA), educational data mining (EDM) and learning analytics and knowledge (LAK). Academic analytics (AA) is a field concerned primarily with organisational efficiencies derived from the intelligent use of business data in the educational context (Chacon, Spicer, & Valbuena, 2012), notably around student retention and faculty effectiveness (Campbell & Oblinger, 2007). Educational data mining (EDM) is a field heavily influenced by information science's engagement with predictive computer based training methodology, in which large data sets are mined to identify predictive student behaviours, allowing faculty to alter course offerings or services on a cohort level. The overlaps between the fields of enquiry are malleable and many influential voices advocate for greater exchange and collaboration between them (Siemens & Baker, 2012).

Why Learning Analytics Matters to Students and Learning Designers

LAK is closely associated with both the AA and EDM fields but with a focus on the individual or personal learning journey. Learning analytics is the process of collecting, measuring, analysing and reporting data on the learner's engagement with learning and, to a lesser extent, on the context of the learner, with a view to optimising both. LAK is concerned with how students develop competence and seeks to identify successful patterns of behaviour, relate that behaviour to known social variables, and identify probable future 'optimal' learning experiences. Data analysis, in the form of visualisations, models or maps, then supports adjustments to the learning environment or the individual learner trajectory to ensure an optimal learning opportunity.

LAK demonstrates a great deal of concern with semantic analysis and, increasingly, with contextual conditions that impact on the learner. There is a focus on how students develop competence, often by acknowledging the social dimensions of learning, and seeks to identify and facilitate optimal social engagement (Buckingham Shum & Ferguson, 2012). Concerned with 'collecting traces that learners leave behind and using those traces to improve learning', both the fields of data mining and visualisation are significant contributors to effective LAK (Duval & Verbert, 2012). Making sense of individuals' behaviour and 'optimising' that behaviour within a given (possibly shifting) context against a backdrop of significant social variation, LAK is the exploration of the connections between factors. Much of the current research focus is on examining the validity of connection interrogation techniques (Guba & Lincoln, 2005).

Significant learning analytics research is required around the design of learning content and its adaptivity (Vandewaetere, Vandercruyssen, & Clarebout, 2012), on the responses and reaction to evolving learning spaces and roles (Atkinson, 2013), and on specific affordances within learning systems (Education Growth Advisors, 2013). However, the most evident data flowing from any learner's engagement with a virtual learning system is likely to be in terms of intervention and adaption (does the student ask for help, does the student follow guidance) and in the field of assessment (Marinagi, Kaburlasos, & Tsoukalas, 2007; Rozali, Hassan, & Zamin, 2010; Silva & Restivo, 2012).

Designing for Learning, Teaching and Analytics

For any LAK system to be capable of interpreting student behaviour and acting on it, the learning activities undertaken by students need to be able to be disaggregated, mapped against desired outcomes, labelled against specific objectives and linked to specific tools and skills. Frameworks to establish quality indicators for learning analytics platforms and tools are emerging (Scheffel, Drachler, Stoyanov, & Specht, 2014), but any LAK models rely on a measurement of engagement. However, this lacks the finesse required for students to adjust to the student's individual context. Simply reminding a student to complete a neglected activity risks being demotivating. Much of higher education lacks alternatives. Knowing, for example, that a student watches and listens to all audio-visual elements in a course unit but neglects readings may prompt the learner to interrogate their study patterns. Are they studying on the train but find reading difficult in that context? Under these circumstances further information might be imparted through their preferred media or they might be advised to consider a text-to-speech application. Alternatively, perhaps the student could be encouraged to timetable in required reading. Regardless, learning should be presented in a context that suits the learner wherever possible.

This requires learning designers, more often faculty themselves, to anticipate both the optimum media and activity mix to enable students to meet the learning outcomes prescribed and the alternatives. Articulating optimal, and alternative, pathways through learning content and activity is not as easy as it might at first appear. This challenge is evidenced by the paucity of alternative assessment provisions in most University courses (Williams, 2014). Disaggregating learning objectives into its constituent elements, activity and tools, is a precondition for a systematic presentation of alternatives. Most faculty find this challenging and toolkits serve a valuable function in reconciling practice with pedagogical theory (Conole & Fill, 2005).

For students to accept these learning analytically driven pathways, I suggest that an annotated advanced organiser is the most suitable means available. Organisers ensure students have a clear idea of the learning completed and the learning required, ensuring they do not use valuable 'working memory' to retain syllabus structures in mind when there is no need to do so (Jong, 2010). Advanced organisers also enable students to see connections between concepts, themes or topics and develop a relational awareness not possible without such visual representations as well as supporting them in planning their workload, timing engagements and planning for activities they anticipate to be challenging (Atkinson, 2011)

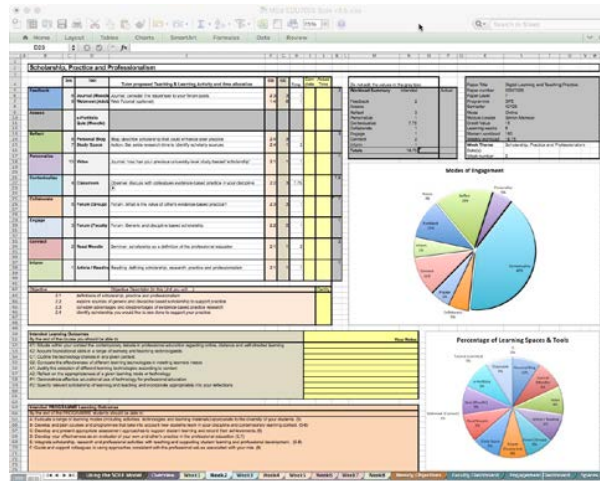


Figure 1 – Excel view of a single topic view of the advanced organiser for the SOLE Toolkit

Empowering students to see their progress and their future engagements is a fundamental part of effective design with future learning analytics in mind. The Student-Owned Learning Engagement (SOLE) model (www.solemodel.org) is a learning design model that also produces a toolkit in the form of an open and editable Excel workbook. It can allow students to use it as an advance organiser and for faculty to design and guide students through optimal pathways (Atkinson, 2011).

Learning designers use the Excel workbook to design a constructively aligned course on a unit, topic or weekly basis (learning outcomes are mapped to topic level objectives), identifying activities across nine modes of engagement, and identifying the tools used. In doing so, a student sees clearly what they need to do, the suggested (but optional) sequence, the tools they should use and the mode of engagement anticipated. This generates two visual representations as pie charts, one displaying the modes of engagement and the other the tools of engagement, for each topic or weekly sheet. The intention here is to make learning a transparent process in which the learner chooses the extent to which they opt to engage, both in modes and with tools, and to make choices of future course selection based their own metacognitive development. The design is flexible enough to be implementable in the majority of VLE platforms.

The mapping of intended learning outcomes (ILO) for a course or module to an individual topic or weekly objectives means that every activity that a student is encourage to engage in will be 'traceable' to the module ILOs. Aggregating the data from completed Excel workshops allows learning designers to identify where 'misjudgements' on the guidance for time allowances might be corrected, or to re-balance the tools being used to ensure modules are as inclusive as possible. Clearly the toolkit has advantages of use being based on unrestricted Excel workbooks, compatible with other spread sheet applications, but it has the disadvantage that is can be 'broken' if cells are over written. Aggregating data would be easier if the toolkit were also fully integrated into back end systems, and this is the focus for future research.

Conclusions

The implication is that each of these representational challenges, organisers, learner validated content, badges and aggregators, must also take into account the different contexts in which learners approach their learning experience. Gender, ethnicity, cultural milieu, language, will all impact on the degree to which a student wants to 'see' their learning journey mapped out in front of them, to have a 'machine' determine their next learning steps, or to be re-directed to correct an 'error' or deficiency in performance. We risk forgetting how fundamental assumptions about knowledge and the nature of learning underpin all our personal approaches to the learning experience; our personal epistemology matters greatly in any self-directed learning approach (Frambach, Driessen, Chan, & van der Vleuten, 2012). The advantages of representing analytical data to students is not so difficult to grasp, the challenges of doing so are significant.

As learning designers, instructional designers and faculty, we must design units of learning that can be disassembled and reconstructed in meaningful ways to enable the LAK algorithms to work.

Experiences from early reusability projects demonstrated that learning content needed to be deliberately structured, assembled from carefully labelled parts, in such a way that the context of use could be recorded, interpreted and amended, and reuse made of all or part of the object (Churchill, 2007; Lukasiak et al., 2005; Muzio, Heins, & Mundell, 2002). The challenge for many current faculty and learning designers is that a granular model of design used by the SOLE Model relies less on raw 'content' than on the articulated relationships between different hermeneutical units, tools and modes of engagement within any given learning unit. The SOLE model and toolkit is not therefore simply a tool, it is a way of working.

However sophisticated the learning analytics platforms, algorithms and user interfaces become in the next few years, it is the fundamentals of the learning design process which will ensure that learning providers do not need to 're-tool' every 12 months. Much of the current commercial effort, informed by 'big data' and 'every-click-counts' models of Internet application development, is largely devoid of any educational understanding. Enquiries into discourse analysis, social network analysis, motivation, empathy and sentiment study, predictive modelling and visualisation, and engagement and adaptive uses of semantic content (Siemens, 2012) inform learning design itself. Grounded in meaningful pedagogical and andragogical theories of learning, these fields will ensure that technology solutions deliver significant and sustainable benefits. The SOLE model is an attempt to lay the foundations of learning designs that empower the learner with the own ability to make adjustments to their personal learning eco-system in partnership with learning analytics tools.

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